wjert, 2021, Vol. 8, Issue 2, 01-20. *Review Article* ISSN 2454-695X

World Journal of Engineering Research and Technology

WJERT

www.wjert.org SJIF Impact Factor: 5.924

ADVANCES OF MACHINE LEARNING IN ELECTROMYOGRAPHY (EMG) SIGNAL CLASSIFICATION

Nahla F. Abdel-Maboud[a]*, Marco Alfonse Tawfik[a], Silvia Stoyanova Parusheva[b] and Abdel-Badeeh M. Salem[a]

[a]Department of Computer Science - Faculty of Computer and Information Sciences -Ain Shams University - Cairo – Egypt.

[b]Department of Computer Science - University of Economics - Varna – Bulgaria.

Article Received on 24/11/2021 **Article Revised on 14/12/2021** **Article Accepted on 04/01/2022**

***Corresponding Author**

Nahla F. Abdel-Maboud

Department of Computer Science - Faculty of Computer and Information Sciences -Ain Shams University - Cairo – Egypt.

ABSTRACT

In the last decades artificial intelligence techniques are used widely by researchers of neuromuscular disorders to increase the diagnostic performance and accuracy. The Electromyography (EMG) is a commonly used technique to record and analyse myoelectric signals. The processing and classification of EMG signals play a major role in the diagnosis of neuromuscular disorders such as Amyotrophic Lateral Sclerosis (ALS).The article aims to give a brief explanation of the different feature extraction and classification techniques that have been applied for the diagnosis of neuromuscular disorders through EMG signal analysis, and presents a review of the recent applications in this field. Wavelet Transform (WT), Principal Component Analysis (PCA) and Empirical Mode Decomposition (EMD) are the most common used feature extraction techniques. Classification techniques such as Artificial Neural Network (ANN), Multilayer Perceptron (MLP), Support Vector Machine (SVM), K-Nearest neighbours (kNN) and deep learning re used to classify EMG signal.

KEYWORDS: EMG electromyography, Feature extraction, Classification, Neuromuscular disorder, Machine learning, Artificial intelligence.

1. INTRODUCTION

Machine learning is based on recording and loading signals data into the machine to be automatically analysed. This analysis shows the difference between the normal and abnormal signals to recognize any disorders in the human body. Machine learning is a promising approach in biomedical engineering for disease classification. The machine learning focuses on extracting information from the signals specified in raw data based on mathematical operations including applying or developing signal analysis tools. Such tools can be useful for biomedical engineering if they are extended to handle big data related to medical operations. Recently, the biomedical signals can be analysed in multiple dimensions since the machine learning techniques have been improved in all fields considering classification and supported decision makers (Alaskar et al., 2014; Balli et al., 2010; Chen et al., 2010). An example of the machine learning techniques used in the diagnosis and disorder detection is supervised learning tools (Zheng et al., 2009; Shahbakhi et al., 2014; Shetty et al., 2016). To improve the performance, the machine learning techniques can be used in biomedical field for computer-aided diagnosis. They are trained on some data set and minimize the large time series signals to optimal discriminated features (Übeyli et al., 2009).

EMG is a valuable diagnostics tool used to study the electrical signals generated in a muscle during its contraction providing information about neuromuscular activities (Reaz et al, 2006). Over the last decades, the EMG has been used extensively by physicians and researchers for characterization of neuromuscular disorders. Neuromuscular disorder is a term used to refer to a wide range of diseases that affect the neuromuscular junctions, nervous system or muscle fibers. The ALS is a progressive neurodegenerative disease that influences the spinal cord and belongs to one type of neuromuscular disorders called motor neuron diseases. The myopathy diseases are another critical type of neuromuscular disorders that includes group of disorders affecting skeletal muscle tissue (Yousefi et al., 2014). The proper and accurate diagnosis of these diseases is very important for their management and treatment in the early stage.

For neuromuscular disorders to be diagnosed using EMG data, the signals must be processed and decomposed, and then significant features should be extracted and classified. This paper presents a review of several classification and feature extraction techniques and its application on EMG signal for diagnosing neuromuscular disorders.

In section 2, we review in brief the different methods used for EMG signal features extraction and classification. In section 3, we present a review of some studies employed these methods for diagnosing neuromuscular disorders based on EMG signal analysis. Finally, conclusion and future work are included in section 4.

2. Emg signal analysis

EMG signal is a biomedical signal that measures the electrical currents generated in a muscle during its contraction producing the neuromuscular activity of that muscle (Chowdhury et al., 2013).

Motor Unit (MU) is the smallest functional unit that can describe the neural control during the muscle contraction process. The group of action potentials generated from all muscle fibers of a motor unit is called Motor Unit Action Potential (MUAP). The MUAPs can be measured in two different techniques, non-invasive and invasive. The non-invasive technique is performed by placing EMG electrodes directly on skin surface whereas in the invasive technique the EMG signals are obtained from the needle electrodes which penetrate muscle tissue. However the non-invasive technique seems more comfortable but it only records the summation of activities from multiple motor units. On the other hand, the invasive technique can record potentials of single motor unit providing more information about muscle activity. Many researchers use the EMG signal as a source of information to develop neuromuscular disorders diagnostic systems. They perform pre-processing on raw signal acquired by the EMG electrodes, extract significant features then apply a classification technique to classify the input signal into different groups (i.e., healthy, myopathy, and ALS patients). Figure 1 shows the main phases for neuromuscular disorders diagnosis based on EMG signal analysis.

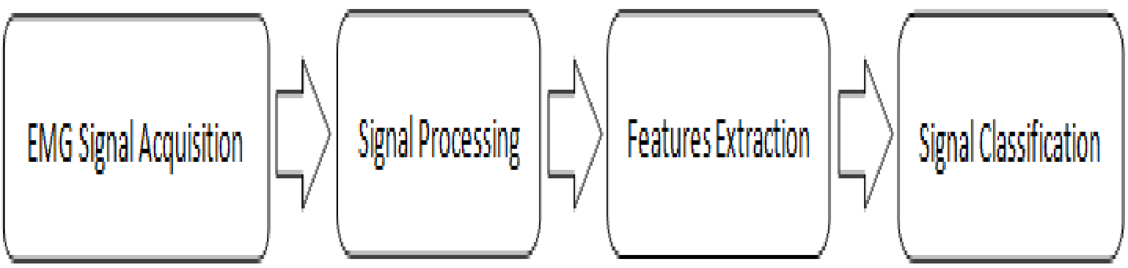

Figure 1: Phases for diagnosing neuromuscular disorders diagnosis through EMG signal analysis.

2.1 EMG Features extraction techniques

After EMG signal acquisition, the next stage is to extract significant features from the signal to be used as input to the classification stage. Features extraction and selection plays a major role to obtain a better classification performance for neuromuscular disorders diagnosis.

In general, there are three types of features that can be extracted from a non-stationary signal like EMG; Frequency Domain (FD) features, Time Domain (TD) features and Time-Frequency Domain (TFD) features.

Analysing the TD features is based on analysing signal amplitude that is a function of time and depends on muscle conditions and types during the observation. This kind has the lowest analysis complexity and does not require additional signal transformation. The FD features are computed by applying the parametric methods to the power spectrum density of the signals. More information can be obtained by combining both TD and FD leading to TFD features that characterize frequency variation at different time locations on the signals (Nazmi et al., 2016).

Several studies used methods such as wavelet transform, empirical mode decomposition, principle component analysis and cepstral analysis to extract TD, FD or TFD features from EMG signals. In the following section, we briefly discuss each of these methods.

2.1.1 Wavelet Transform (WT)

The WT represents the time function in simple building blocks to solve the non-stationary signals problems. Such blocks are set of functions derived from a wavelet by translation and dilation operations. This method provides an optimal time frequency resolution in all frequency ranges (Kehri et al., 2016). The Discrete Wavelet Transform (DWT) can be applied to multiple biomedical engineering signal processing applications, such as EMG signal processing, as it provides both time and frequency information at the same time. While the Discrete Fourier Transform (DFT) is localized only in frequency domain (Tafhim Khan & Tahseenul Hasan, 2015). DWT has been used by many researchers to extract features from EMG signal for neuromuscular disorders classification (Abdel-Maboud et al., 2015; Khan et al., 2016; Meena & Bansal, 2016; Subasi et al., 2018).

2.1.2 Principal Component Analysis (PCA)

PCA is a statistical technique that has been used widely in biomedical signals analysis. It is a simple non-parametric method used for extracting relevant information from high dimensional dataset (Kehri et al., 2016). PCA can find similarities and differences in data patterns. By finding patterns, the data dimensionality can be reduced without losing much information (Shaw & Bagha, 2012). For these reasons, PCA is the most common technique used for dimensionality reduction and can be used efficiently in analysing large datasets of EMG signals.

2.1.3 Empirical Mode Decomposition (EMD)

The EMD technique does not use an external function for decomposition but it is a self-adaptive time-space analysis method that decomposes non-linear and non-stationary signals such as EMG signal. It can preserve the time domain while decomposing the signal into several Intrinsic Mode Functions (IMFs). IMFs should satisfy two main conditions 1) the number of zero-crossings and the number of extrema should differs only by one and 2) the local average between the upper envelope and lower envelope is zero. The EMD has a wide range of applications in audio, biomedical and image processing (Chowdhury et al., 2013). In particular, EMD is useful in analysing complex non-linear and non-stationary signals.

2.2 Classification techniques

Many researchers used classification techniques including neural networks (Shaw & Bagha, 2012; Elamvazuthi et al., 2015; Vallejo et al., 2018), support vector machines (Goen, 2014; Kehri et al., 2016), random forests (Yaman & Subasi, 2019), fuzzy logic (Shijiya & Thomas, 2016; Khan et al. 2016) and deep learning (Sengur et al., 2017). This section provides a brief review about each of these techniques.

2.2.1 Artificial Neural Networks (ANN)

ANNs are widely used in biomedical engineering to analyse signals due to their effectiveness, fast recognition and real-time diagnosis. The ANNs are trained by giving examples, and not interrupted by personal emotional state, fatigue, or external factors (Micheli-Tzanakou, 2000).

Their powerful advantage is the ability to emulate the system complexity with high accuracy in the form of either linear or non-linear analogy in input and output data. The information is collected from external source and transferred to adjacent layers using transfer functions and connection parameters.

The Back-Propagation (BP) based neural network has wide applications in pattern recognition and signal processing (Elamvazuthi et al., 2015; Vallejo et al., 2018). It is a multi-layer architecture. So the information is transferred to the input layer which is connected to multiple hidden layers with weights and is further connected to output layer with weights which gives the desired output. In case of dissimilarity between the desired and actual outputs, the error is evaluated to update the weights and the process is repeated until the error is eliminated (Kumar Singh et al., 2017).

In biological networks, the main element that performs the computation is the neuron. The input signals are handled by the connection weights, and then combined and compared with a threshold value which is bias of the neuron. The output signal is controlled by an activation function. In multi-layer feed-forward network there exist hidden layers between the input and output layers, and the neurons are linked layer-by-layer (Zhou, 2012).

2.2.2 k-Nearest Neighbours (kNN)

kNN is a simple classifier in which a distance function such as Euclidean distance function is evaluated between a test set and k-neighbouring points from normal and diseased subjects. The labels of k-nearest pattern are used in classifying the test record considering the k values providing best classification accuracy.

The kNN can calculate the distances between the test record and the signal records in ascending order showing the k records with the smallest distance. On the other hand, it can be used in pattern recognition to classify objects based on the closest training examples defined in the feature space (Bhuvaneswari & Kumar, 2016; Fattah et al., 2013).This approach is time consuming and depends on learning by relationship via the Euclidean distance, and the unknown record is chosen as the most well-known class among its k-nearest neighbours (Witten et al., 2011).

2.2.3 Support Vector Machine (SVM)

It is the most accurate binary classifier used for pattern recognition and uses a hyper plane to separate different classes of data by characterizing the margin. SVM can be either linear or non-linear model. In the linear one, the data points are separated by a gap and straight hyper planes can be used in classes division. In some cases, linear SVMs are not efficient and the non-linear classifiers are suggested instead. In non-linear SVM Classification, multiclass classifications use One-Against-All (OAA) and One-Against-One (OAO) relationships (Witten et al., 2011).

2.2.4 Deep Learning

The deep learning has the ability to deal with large, high-dimensional data with a large number of features. It has several models such as auto-encoders, deep belief network, deep Boltzmann machines, convolutional neural networks and recurrent neural networks (Alaskar, 2018). Convolution Neural Networks (CNNs) are the most successful deep learning model. They are self-learned and self-organized networks and are used recently in biomedical signals classification.

3. Advances of machine learning in neuromuscular disorders diagnosis

The Probabilistic Neural Network (PNN) has been used by Shaw and Bagha (2012) to classify the surface EMG signal to distinguish between normal, myopathy and neuropathy subjects. Features have been extracted from the signal using PCA. The PNN obtained accuracy performances varies between 85- 98% with respect to pattern length and yield to average classification rate of 91.72%.

Elamvazuthi et al. (2015) applied multi-layer perceptron neural network with back-propagation algorithm on EMG signals acquired from bicep muscles of 15 subjects (5 healthy, 5 myopathy and 5 neuropathy). For each class, 100 samples were randomly taken from the signal (60 for training, 20 for validation and 20 for testing). Feature extraction was performed using five different feature extraction techniques such as Root Mean Square (RMS), Zero Crossing (ZC), AR, Waveform Length (WL) and Mean Absolute Value (MAV). The output data from the feature extraction process were used to create five different datasets (healthy / unhealthy (abnormal), healthy / myopathy, healthy / neuropathy, myopathy / neuropathy and healthy / myopathy / neuropathy). This work achieved five different classification accuracies for each group using RMS, ZC, AR, WL and MAV features. The group of healthy and unhealthy subject obtained the highest classification accuracy of 82.5% using RMS and WL. For the group of healthy and myopathy subjects, AR yields the best result with 83%. For the third group, AR and RMS gave the top result with 83.5%. For the fourth and fifth groups, the AR technique produced the best result with accuracies of 82.5% for group of myopathy and neuropathy subjects and 86.3% for healthy, myopathy and neuropathy group. The AR proved to be a good feature extraction technique by achieving the best accuracy for four groups of five.

Vallejo et al. (2018) used both DWT and fuzzy entropy for feature extraction to detect neuromuscular disorders from EMG signal. The study was performed on a database of EMG signals acquired from 10 healthy subjects, 7 myopathy volunteers and 8 ALS patients. The signals were registered from vastus medialis, biceps brachii, and deltoideus muscles and filtered using high and low filters set at 2 Hz and 10 kHz. Only 120 registers were selected (40 per class) from a total of 395 registers. Firstly, DWT was used to decompose each recording into different frequency bands with a mother wavelet Daubechies 8, then statistical functions (arithmetic mean of the absolute values of the coefficients in each sub-band, standard deviation and kurtosis) and energy features (energy, Hilbert Shannon energy and Teager energy operator) were extracted and a total of 56 features were obtained. After that, fuzzy entropy was performed on the previously achieved features as a relevance analysis technique so that it can reject redundant and irrelevant features and select only the relevant features. Then, a feedforward neural network with log-sigmoid activation function was used for the classification process. The used ANN consisted of four layers and seven neuron networks in each layer. Seventy hundred of the data was used for training and thirty hundred for validation. The results showed an accuracy of 98%.

Bozkurt et al. (2016) used two types of neural networks, combined neural network and Feed forward Error Back-propagation Artificial Neural Network (FEBANN), to classify EMG signal into healthy, myopathy, or neurogenic classes. The proposed method was tested on 1200 EMG signal patterns acquired from 27 subjects (7 healthy, 7 myopathy, and 13 neurogenic subjects), 400 patterns for each class divided into 300 for training and 100 for testing. The EMG signal was obtained from the biceps brachii muscle during a little voluntary contraction for 5 seconds and sampled at 20 kHz with 12-bit acquisition data card resolution. Several AR parametric techniques, such as Yule-Walker, Covariance, Modified covariance and Burg techniques; and subspace-based methods such as multiple signal classification and eigenvector techniques were used to extract features from MUPs of EMG signals. Among these methods, the eigenvector provided the highest performance. The FEBANN with eigenvector features obtained its highest classification accuracy of 93.3, where CNN obtained higher accuracy of 94% with the same feature extraction method.

The ANN was also used by Kumar Singh et al. (2017) to classify EMG signal based on features generated from empirical mode decomposition process namely mean, standard deviation, variance and entropy of the IMFs. This technique was applied on a dataset consists of 51 healthy, 111 myopathy and 148 neuropathy subsets. For each subset, 1000 samples were used for signal classification. The signals were acquired from tibialis anterior muscle using a 25 mm needle electrode at 50 kHz sampling rate. The statistical features of IMFs achieved better classification accuracy of 94% compared to other feature extraction techniques such as multi-scale entropy, WT, AR coefficients and statistical features.

Bhuvaneswari and Kumar (2016) used kNN to distinguish healthy and neuropathy subjects from EMG patterns. They used a dataset consists of 25 records from healthy subjects without the history of neuromuscular disease, subjects with long lasting history of polymyositis and subjects with chronic low back pain and neuropathy due to right L5 radiculopathy. The signals were acquired using a Medelec Synergy N2 EMG Monitoring system with a sampling rate range from 20 Hz to 50 KHz. The cepstral analysis has been used for features extraction. Cepstral analysis is a nonlinear signal processing technique that handles the signal real part and is calculated by the inverse of the log of the discrete Fourier transform signal. At first, signal was transformed from time to frequency domain. Then the spectral representation of the signal was decomposed by wavelet decomposition using low pass filter to obtain approximation coefficients and high pass filter for detail coefficients. Then, features were extracted using cepstral analysis process. After that, features dimensions were reduced using Minimum Redundancy Maximum Relevance (MRMR) then feed as inputs to kNN classifier. The classification accuracy varies dependent on the selected features and the used dimensionality reduction method.

The kNN was also used by Fattah et al. (2013) to classify ALS and normal signals. The DWT features have been extracted from EMG frame then classified using the kNN classifier. The proposed method was tested on EMG signals of 5 normal subjects and 5 ALS patients, each class consisted of 15 datasets. The DWT coefficients with higher values and their mean and maxima have been used to reduce the feature dimension of DWT for detection of ALS EMG signals. These three features obtained outstanding classification accuracy of 100% where Zero Crossing (ZC) and Mean Frequency (MF) features obtained 72.2% and 69.5% respectively.

PU et al. (2018) also employed kNN to classify healthy persons and ALS patients. Tunable-Q factor Wavelet Transform (TQWT) has been used to extract features from EMG signal for identifying of healthy and ALS signals. The TQWT can decompose EMG signal into sub-bands then statistical features such as mean absolute deviation, interquartile range, kurtosis, mode, and entropy have been computed from these sub-bands and used as inputs to the kNN classifier. In addition to kNN, least squares support vector machine classifier has been also used to classify the same features and a comparison was made between both classifiers' performances. The dataset used to test the proposed method contains 89 ALS and 133 healthy EMG signals which have been amplified at a frequency range of 5 Hz-5 kHz filter settings and sampled at a frequency of 10 kHz. Classification accuracy for each classifier varied with respect to the TQWT sub-bands. The LS-SVM classifier obtained classification accuracy of 74.55-90.45%. On the other hand, the kNN showed better performance by achieving higher classification rate of 90.45-95%.

Goen (2014) employed binary SVM for recognition of normal, myopathy and neuropathy subjects through EMG signal analysis. The proposed technique has been tested on an EMG dataset that contains 11 myopathy, 11 neuropathy and 12 healthy subjects. At first, EMG signal have been decomposed into MUAPs. Then the statistical features have been computed from the MUAPs and fed to the classifier. Binary SVM, SVM ensemble and RBFNN have been used for 2-class (normal / diseased) and 3-class (normal / myopathy / neuropathy) recognition. SVM ensemble provided the best performance for both 2-class and 3-class classification with classification rate of 90.1 and 91.2 respectively.

Tafhim Khan and Tahseenul Hasan (2015) made a comparison between kNN and SVM classifiers in classifying healthy, myopathy and ALS EMG signals. The authors used DWT to extract wavelet features from the signals. Applying kNN classifier on the extracted features obtained an accuracy of 82%, whereas SVM classified these features with accuracy of 92.33%. In this work, SVM proved its efficiency in classifying EMG signal compared to the kNN technique.

Artameeyanant et al. (2016) proposed a method based on a Normalized Weight Vertical Visibility Algorithm (NWVVA) to extract features from EMG signal for myopathy and ALS classification. This method focuses on extracting sampling nodes based on sampling theory and obtaining features from relations between the vertical visibility nodes and their amplitude differences as weights. Selective statistical mechanics and measurements were used to calculate the statistical features. Then these features were used as input to the classifier. In this study; kNN, MLPNN, and SVM classifiers have been used to classify these data and a comparison was made between their classification accuracies. The kNN, MLPNN, and SVM classifiers yielded accuracies of 96, 97, and 98%, respectively. In this work, the SVM classifier obtained the highest accuracy among the three classifiers.

Kehri et al. (2016) used a combination of feature extraction techniques with different classifiers to compare their performance in EMG signal classification into normal and abnormal subjects. The used EMG signals were acquired from brachial biceps muscles through standard needle electrode. The sampling rate of the signal is 10 kHz. The dataset consists of 5 normal and 5 abnormal signals. The applied classification techniques are DWT+ANN, PCA+ANN, DWT+PNN and DWT+SVM and they obtained classification accuracies of 90.4%, 92.4%, 93.05% and 94.28%, respectively. The classification of DWT features using SVM classifier obtained the highest accuracy rate.

Subasi et al. (2018) compared between different classification techniques as single and bagging ensemble classifiers. The EMG signals used in this comparison were recorded using a concentric needle electrode from the biceps brachii muscle and sampled at 20 kHz for 5 seconds. The signals were collected from seven healthy, seven myopathy and thirteen neuropathy subjects. Firstly, the signals have been decomposed using DWT into wavelet coefficients. Then, the features dimension has been reduced by calculating statistical features namely MAV, SD, average power, ratio of the absolute mean values, skewness, and kurtosis. Different classifiers such as SVM, ANN, kNN, Classification and Regression Trees (CART), C4.5, Reduced Error Pruning (REP) tree, Logical Analysis of Data (LAD) tree and random tree have been used. Compared to other methods, SVM provided the highest classification accuracies of 98.96% and 99% for both single classifier and bagging ensemble classifier, respectively.

Sengur et al. (2017) proposed a deep learning based method to classify the 2d time frequency images of ALS and normal EMG signals. The CNN is used for classification of each input image based on the spatial information of the pixels incorporated to the network nodes. The CNN consists of convolution and pooling layers which construct the features responsible for the classification by the fully connected layer. The parameters are tuned during the training stage that is controlled by the convolution back propagation algorithm. A new learning strategy called reinforcement sample learning strategy was used to increase the efficiency and speed up the training process. In this study, spectrogram, continuous wavelet transform, and Smoothed Pseudo Wigner–Ville Distribution (SPWVD) have been utilized for transforming EMG signals into its time–frequency representation. The proposed method was tested on a dataset that comprises of 89 ALS and 133 normal EMG signals with 24 kHz sampling frequency. The CNN achieved 96.80% classification accuracy.

Abdel-Maboud et al. (2015) proposed a hybrid classifier for neuromuscular disorders diagnosis. This classifier was tested on a dataset of EMG signals of 5 normal subjects, 5 myopathy and 5 ALS patients. The DWT has been applied for EMG signal analysis. Then RMS, MAV, ZC, SSC and STD statistical values have been computed. The hybrid classifier consisted of two different types of classifiers which are SVM and ANN. Each of these classifiers was applied on all the different features separately to classify one class against the other classes. For ALS, the highest classification rate of 98% was obtained by using the SVM classifier with the RMS feature as input. On the other hand, the ANN proved its capability on classifying myopathy subjects with accuracy rate of 86.6%. The overall accuracy of this hybrid classifier is 85.5%.

The fuzzy logic and the ANN have been used together by Shijiya and Thomas (2016) to improve the classification accuracy of EMG signals of normal, ALS and myopathy. They employed spectral features such as MF, Mean Power (MP), Total Power (TP), Peak Frequency (PF), Wavelet Energy (WE), Wavelet Mean (WM), Wavelet Average Power (WAP), Wavelet Standard Deviation (WSD) and temporal features namely MAV, Variance, Squared Integral (SI) and Integrated EMG (IEMG). The dataset used in this work consists of 75 signals from each class of the three classes in addition to 15 signals from Parkinson diseased patients and 20 signals belonged to Huntington's patients. The classification accuracy obtained by using ANN is 93.46% and by using ANN with fuzzy logic is 94.61%. It is noticeable that fuzzy logic with ANN improved the accuracy compared to ANN classifier.

Khan et al. (2016) also proposed a multi-classifier method to enhance the EMG signal classification accuracy for neuromuscular disorders identification. They applied both time domain and time-frequency domain features on MUAPs extracted from EMG signal. The proposed method was tested on a dataset of 150 EMG signals obtained from normal, neuropathic and myopathic subjects, 50 samples of each class. Different single and multiple classifiers of SVM and kNN were investigated. The multi-classifier method proposed in this study obtained average accuracy of 97% using time-frequency feature and weighted kNN provided accuracy of 95%.

SVM-kNN classifier also proved its efficiency in other works as showed in (Meena & Bansal, 2016) where the EMG signal has been analyzed using coiflet wavelet transform and computed statistical features such as energy, mean and standard deviation. Then these features used to classify normal, myopathy and neuropathy signals. The dataset used in this work includes 500 signals from each class (350 for training and 150 for testing). Varies classifiers namely SVM and SVM-kNN were utilized to classify the extracted features to select the classifier with the highest accuracy. SVM obtained 92% accuracy rate whereas SVM-kNN achieved higher accuracy of 95%.

Yaman and Subasi (2019) made a comparison between different bagging and boosting ensemble learning methods to classify EMG signals for diagnosis of neuromuscular disorders. At first, they calculated the Wavelet-Packed Coefficients (WPC) from the signals. Then, six statistical features which are; MAV, average power, SD, ratio of the absolute mean values, skewness, and Kurtosis have been computed from WPC of the signals and used as inputs to the classifier. The dataset used in this comparison consists of 7 healthy, 7 myopathy, and 13 neuropathy subjects. The combination of Adaptive Boosting (AdaBoost) learning algorithm with random forest ensemble classifier achieved the best result with 99.08% accuracy.

All of the studies discussed in this section are summarized in Table 1, 2, 3 and 4 which provide the studies' objectives, feature extraction methods, classification techniques, datasets, and classification accuracies.

Table 1: Artificial neural network in neuromuscular disorders classification.

Reference	Objective	Feature extraction method	Classifier	Dataset	Accuracy (%)
Shaw and Bagha (2012)	Healthy/Myopathy/ Neuropathy	PCA	ANN		91.72
Elamvazuthi et al. (2015)	Healthy/Myopathy/ Neuropathy	AR, RMS, ZC, WL, MAV	Multilayer perceptron artificial neural network	EMG lab (Nikolic, 2001)	86.3 (AR) 78.7 (RMS) 76.3 (ZC) 75.7 (WL)

			(MLP-ANN)		82 (MAV)
Vallejo et al. (2018)	Healthy/Myopathy/ ALS	Features extracted from Discrete Wavelet Transform (DWT) + Fuzzy entropy	ANN	EMG lab (Nikolic, 2001)	98
Bozkurt et al. (2016)	Healthy/Myopathy/ Neuropathy	Parametric and subspace-based methods Features	FFBP-NN combined neural network	Neurology Department of Gaziantep University	93.3 (FFBP-NN) 94 (combined neural network)
Kumar Singh et al. (2017)	Healthy/Myopathy/ Neuropathy	Features of the intrinsic mode functions (IMFs) generated by empirical mode decomposition (EMD) process	FFBP-NN	Physionet (Goldberger et al., 2000)	94
Sengur et al. (2017)	Normal/ALS	Time-frequency images generated using The Spectrogram, continuous wavelet transform and smoothed pseudo Wigner–Ville	CNN	EMG lab (Nikolic, 2001)	96.80

Table1 demonstrates that ANNs are used widely in EMG signal classification and achieved high accuracy rates in neuromuscular disorders identification. Moreover, ANN shows better classification accuracy in EMG signal classification using DWT and fuzzy entropy for small database and when a cross validation test was performed.

Table 2: kNN in neuromuscular disorders classification.

Reference	Objective	Feature extraction method	Classifier	Dataset	Accuracy (%)
Fattah et al. (2013)	Normal/ALS	Features extracted from DWT	kNN	EMG lab (Nikolic, 2001)	100
Bhuvaneswari and Kumar (2016)	Healthy/Neuropathy	Cepstral features	kNN	Physionet (Goldberger et al., 2000)	Different accuracies based on number. of features
PU et al. (2018)	Normal/ALS	Features extracted from TQWT	kNN	EMG lab (Nikolic, 2001)	95

According to Table 2, we can notice that the authors proposed kNN to classify normal and neuropathy subjects and obtained best classification accuracy when feature extraction is performed using DWT method than other methods.

Table 3: Support vector machine in neuromuscular disorders classification.

Reference	Objective	Feature Extraction method	Classifier	Dataset	Accuracy (%)
Goen (2014)	Normal/Pathogenic Myopathy/Neuropathy Normal/Myopathy/Neuropathy	MUAPs features	SVM ensemble		90.1 (2 classes) 92.3 (2 classes) 91.2 (3 classes)
Tafhim Khan and Tahseenul Hasan (2015)	Healthy/Myopathy/ALS	Features extracted from DWT	kNN SVM	EMG lab (Nikolic, 2001)	82 (kNN) 92.33 (SVM)
Artameeyanant et al. (2016)	Healthy/Myopathy/ Neuropathy	Features extracted using a normalized weight vertical visibility algorithm	kNN MLPNN SVM	EMG lab (Nikolic, 2001) Physionet (Goldberger et al., 2000)	96 (kNN) 97 (MLPNN) 98 (SVM)
Kehri et al. (2016)	Normal/Abnormal	Features extracted from DWT	SVM	EMG lab (Nikolic, 2001)	94.28
Subasi et al. (2018)	Healthy/Myopathy/ Neuropathy	Features extracted from DWT	Bagging ensemble classifier	Neurology Department of	99

			with SVM	Gaziantep University	

From Table 3 it is noticeable that SVM proved its efficiency for multi-class classification. Some studies made comparisons between ANN and SVM and showed that SVM yielded higher accuracy results. On the other hand, bagging and boosting ensemble learning methods obtained approximately a perfect accuracy rate when used for EMG signal classification.

Table 4: Hybrid algorithms in neuromuscular disorders classification.

Reference	Objective	Feature Extraction method	Classifier	Dataset	Accuracy (%)
Abdel-Maboud et al. (2015)	Healthy/Myopathy/ Neuropathy	Time domain features	SVM and FFBP-ANN	EMG lab (Nikolic, 2001)	85.5
Khan et al. (2016)	Healthy/Myopathy/ Neuropathy	Time domain and time-frequency domain features	SVM and kNN		97
Meena and Bansal (2016)	Healthy/Myopathy/ Neuropathy	Features extracted from DWT	SVM and kNN	MIT-BIH database	95
Shijiya and Thomas (2016)	Healthy/ Myopathy /Neuropathy/ Parkinson's disease/ Huntington's disease	Spectral and temporal features	ANN and Fuzzy logic	EMG lab (Nikolic, 2001) Physionet (Goldberger et al., 2000)	94.61
Yaman and Subasi (2019)	Healthy/Myopathy/ Neuropathy	Features extracted from wavelet packed decomposition	AdaBoost with random forests	Neurology Department of Gaziantep University	99.08

Table 4 shows that AdaBoost with random forests shows higher accuracy rate than other hybrid algorithms for classification of EMG signals. Moreover, DWT and wavelet packed decomposition are better feature extraction techniques than spectral and temporal features.

CONCLUSION AND FUTURE WORK

This paper presents an overview of how EMG signal can be used for neuromuscular disorders diagnosis. Several challenges which face researchers in EMG signal analysis are due to signal’s complexion and non-stationary nature. This paper provides a review of recent advances in analysing EMG signal including feature extraction and classification techniques employed to classify healthy, myopathy, and neuropathy subjects. This review shows that various techniques proved significant efficiency in this field, such as DWT for feature extraction and SVM for classification.

For future work, efficient EMG classification method with high accuracy rate can be used in real time neuromuscular disorders diagnostic systems.

REFERENCES

1. AbdelMaboud, N. F., Elbagoury, B., Roushdy, M., & Salem, A. M. A new hybrid classifier for neuromuscular disorders diagnoses. Egyptian Computer Science Journal (ECS), 2015; 39(1): 86-92.
2. Alaskar, H., Hussain, A.J., Paul, F.H., Al-Jumeily, D., Taw k, H., & Hamdan H. Feature Analysis of Uterine Electrohystography Signal Using Dynamic Self-organised Multilayer Network Inspired by the Immune Algorithm. In Huang DS., Bevilacqua V., & Premaratne P. (Eds.), Lecture Notes in Computer Science: Intelligent Computing Theory, 2014; 8588: 760–766. Springer. http://doi.org/10.1007/978-3-319-95957-3_80
3. Alaskar, H. Convolutional Neural Network Application in Biomedical Signals. Journal of Computer Science and Information Technology, 2018; 6(2): 45-59. http://doi.org/10.15640/jcsit.v6n2a5
4. Artameeyanant, P., Sultornsanee, S., & Chamnongthai, K. An EMG-based feature extraction method using a normalized weight vertical visibility algorithm for myopathy and neuropathy detection. Springer Plus, 2016; 5(1). https://doi.org/10.1186/s40064-016-3772-2
5. Balli, T., & Palaniappan, R. Classification of biological signals using linear and nonlinear features. Physio- logical Measurement, 2010; 31(7): 903–920. http://doi.org/10.1088/0967-3334/31/7/003
6. Bhuvaneswari, P., & Kumar, J. S. Electromyography based Detection of Neuropathy Disorder using Reduced Cepstral Feature. Indian Journal of Science and Technology, 2016; 9(8). http://doi.org/10.17485/ijst/2016/v9i8/87899
7. Bozkurt, M. R., Subaşi, A., Köklükaya, E., & Yilmaz, M. Comparison of AR parametric methods with subspace-based methods for EMG signal Classification using stand-alone and merged neural network models. Turkish Journal of Electrical Engineering and Computer Sciences, 2016; 24: 1547–1559. http://doi.org/10.3906/elk-1309-1

8. Chen, X., Zhu, X., & Zhang, D. A discriminant bispectrum feature for surface electromyogram signal Classification. Medical Engineering and Physics, 2010; 32(2): 126–135. http://doi.org/10.1016/j.medengphy.2009.10.016
9. Chowdhury, R., Reaz, M., Ali, M., Bakar, A., Chellappan, K., & Chang, T. Surface Electromyography Signal Processing and Classification Techniques. Sensors, 2013; 13(9): 12431–12466. http://doi.org/10.3390/s130912431
10. Elamvazuthi, I., Duy, N. H. X., Ali, Z., Su, S. W., Khan, M. K. A. A., & Parasuraman, S. Electromyography (EMG) based Classification of Neuromuscular Disorders using Multi-Layer Perceptron. Procedia Computer Science, 2015; 76: 223–228. http://doi.org/10.1016/j.procs.2015.12.346
11. Fattah, S. A., Doulah, A. B. M. S. U., Iqbal, M. A., Shahnaz, C., Wei-Ping Zhu, & Ahmad, M. O. Identification of motor neuron disease using wavelet domain features extracted from EMG signal. Proceedings of IEEE International Symposium on Circuits and Systems (ISCAS), Beijing, 2013; 1308-1311. http://doi.org/10.1109/iscas.2013.6572094
12. Goen, A. Classification of EMG Signals for Assessment of Neuromuscular Disorders. International Journal of Electronics and Electrical Engineering, 2014; 2(3): 242–248. http://doi.org/10.12720/ijeee.2.3.242-248
13. Goldberger, A. L., Amaral, L. A. N., Glass, L., Hausdor, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., &Stanley, H. E. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation, 2000; 101(23): 215-220. [Data Set]. http://doi.org/10.1161/01.cir.101.23.e215
14. Kehri, V., Ingle, R., Awale, R., & Oimbe, S. Techniques of EMG signal analysis and Classification of neuro- muscular diseases. Proceedings of the International Conference on Communication and Signal Processing (ICCASP), 2016. http://doi.org/10.2991/iccasp-16.2017.71
15. Khan, M., Singh, J., & Tiwari, M. A Multi-Classifier Approach of EMG Signal Classification for Diagnosis of Neuromuscular Disorders. International Journal of Computer Applications, 2016; 133(4): 13–18. http://doi.org/10.5120/ijca201690771
16. Kumar Singh, A., Agrawal, N. K., & Gupta, S. Approach for Classification of neuromuscular disorder using EMG signals. International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE), 2017; 5 (5): 9382-9387.

17. Meena, P., & Bansal, M. Classification of EMG signals using SVM-kNN. International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE), 2016; 5(6): 1718-1724.
18. Micheli-Tzanakou, E. The Biomedical Engineering Handbook. Boca Raton, 2000. FL: Chapman and Hall/CRC Press.
19. Nazmi, N., Abdul Rahman, M., Yamamoto, S.-I., Ahmad, S., Zamzuri, H., & Mazlan, S. A Review of Classification Techniques of EMG Signals during Isotonic and Isometric Contractions. Sensors, 2016; 16(8): 1304. http://doi.org/10.3390/s160813
20. Nikolic, M. EMG signal Data for neuromuscular disorders, Detailed analysis of clinical electromyography signals EMG decomposition, findings and ring pattern analysis in controls and patients with myopathy and amyotrophic lateral sclerosis, 2001. [Doctoral dissertation, Faculty of Health Science, University of Copenhagen] [Data Set].
21. Vallejo, M, Gallego, CJ, Duque-Muñoz, L, Delgado-Trejos, E (2018). Neuromuscular disease detection by neural networks and fuzzy entropy on time-frequency analysis of electromyography signals. Expert Systems, 2018; 35: e12274. https://doi.org/10.1111/exsy.12274.
22. PU, K., N, A., S, T., & V, B. TQWT Based Features for Classification of ALS and Healthy EMG Signals. American Journal of Computer Science and Information Technology, 2018; 6(2). http://doi.org/10.21767/2349-3917.100019
23. Reaz, M. B. I., Hussain, M. S., & Mohd-Yasin, F. Techniques of EMG signal analysis: detection, processing, Classification and applications. Biological Procedures Online, 2006; 8(1): 11–35. http://doi.org/10.1251/bpo115
24. Sengur, A., Akbulut, Y., Guo, Y., & Bajaj, V. Classification of amyotrophic lateral sclerosis disease based on convolutional neural network and reinforcement sample learning algorithm. Health Information Science and Systems, 2017; 5(1). http://doi.org/10.1007/s13755-017-0029-6
25. Shahbakhi, M., Far, D. T., & Tahami, E. Speech Analysis for Diagnosis of Parkinson's Disease Using Genetic Algorithm and Support Vector Machine. Journal of Biomedical Science and Engineering, 2014; 7(4): 147–156. http://doi.org/10.4236/jbise.2014.74019
26. Shaw, L., & Bagha, S. Online EMG signal analysis for diagnosis of neuromuscular diseases by using PCA and PNN. International Journal of Engineering Science and Technology (IJEST), 4, 4453-4459.
27. Shetty, S., & Rao, Y. S. SVM based machine learning approach to identify Parkinson's disease using gait analysis. Proceedings of 2016 International Conference on Inventive

Computation Technologies (ICICT), 2016; 1-5. https://doi.org/10.1109/INVENTIVE.2016.7824836

28. Shijiya, S., & Thomas, P. An improved method to detect common muscular disorders from EMG signals using artificial neural network and fuzzy logic. International Journal of Advanced Technology in Engineering and Science (IJATES), 2016; 4(7): 68-75.
29. Subasi, A., Yaman, E., Somaily, Y., Alynabawi, H. A., Alobaidi, F., & Altheibani, S. Automated EMG Signal Classification for Diagnosis of Neuromuscular Disorders Using DWT and Bagging. Procedia Computer Science, 2018; 140: 230–237. http://doi.org/10.1016/j.procs.2018.10.333
30. Tafhim Khan, M., & Tahseenul Hasan, M. Comparison between kNN and SVM for EMG signal Classification. International Journal on Recent and Innovation Trends in Computing and Communication (IJRITCC), 2015; 3(12): 6799-6801. Übeyli, E. D. (2009). Analysis of EEG signals by implementing eigenvector methods/recurrent neural networks.
31. Digital Signal Processing, 19(1): 134–143. http://doi.org/10.1016/j.dsp.2008.07.007
32. Witten, I. H., Frank, E., & Hall, M. A. (Eds.), 2011. Data Mining: Practical Machine Learning Tools and Techniques. Elsevier. https://doi.org/10.1016/C2009-0-19715-5
33. Yaman, E., & Subasi, A., 2019. Comparison of Bagging and Boosting Ensemble Machine Learning Methods for Automated EMG Signal Classification. BioMed Research International, Article 9152506. http://doi.org/10.1155/2019/9152506
34. Youse, J., & Hamilton-Wright, A. Characterizing EMG data using machine-learning tools. Computers in Biology and Medicine, 2014; 51: 1–13. http://doi.org/10.1016/j.compbiomed.2014.04.018
35. Zheng, H., Yang, M., Wang, H., & McClean, S. Machine Learning and Statistical Approaches to Support the Discrimination of Neuro-degenerative Diseases Based on Gait Analysis. In McClean S., Millard P., El-Darzi E., & Nugent C. (Eds.), Studies in Computational Intelligence: Intelligent Patient Management, 2009; 189: 57–70. Springer. http://doi.org/10.1007/978-3-642-00179-6_4
36. Zhou, Z.-H. Ensemble Methods, 2012. http://doi.org/10.1201/b12207